THE UNIVERSITY *of York*

CHE
Centre For Health Economics

GP Supply and Obesity

CHE Research Paper 13

GP supply and obesity

Stephen Morris[a*]
Hugh Gravelle[b]

April 2006

[a] NPCRDC, University of Manchester; and, Tanaka Business School, Imperial College London South Kensington Campus, London SW7 2AZ, UK.
[b] NPCRDC, Centre for Health Economics, University of York, York, UK.
[*] Corresponding author. Tel: +44 (0)20 759 49118. Email address: s.morris@imperial.ac.uk

Background

CHE Discussion Papers (DPs) began publication in 1983 as a means of making current research material more widely available to health economists and other potential users. So as to speed up the dissemination process, papers were originally published by CHE and distributed by post to a worldwide readership.

The new CHE Research Paper series takes over that function and provides access to current research output via web-based publication, although hard copy will continue to be available (but subject to charge).

Acknowledgements

NPCRDC receives funding from the Department of Health (DH). The views expressed are those of the authors and not necessarily those of the DH. We thank Martin Roland, Matt Sutton and Frank Windmeijer for their advice. We are grateful to the AREA project team for assistance with data.

Further copies

Copies of this paper are freely available to download from the CHE website www.york.ac.uk/inst/che/pubs. Access to downloaded material is provided on the understanding that it is intended for personal use. Copies of downloaded papers may be distributed to third-parties subject to the proviso that the CHE publication source is properly acknowledged and that such distribution is not subject to any payment.

Printed copies are available on request at a charge of £5.00 per copy. Please contact the CHE Publications Office, email che-pub@york.ac.uk, telephone 01904 321458 for further details.

Centre for Health Economics
Alcuin College
University of York
York, UK
www.york.ac.uk/inst/che

Abstract

We investigate the relationship between GP supply and body mass index (BMI) in England. Individual level BMI is regressed against area whole time equivalent GPs per 1,000 population plus individual and area level covariates. Using IV models we find that a 10% increase in GP supply is associated with a mean reduction in BMI of around 1 kg/m^2 (around 4% of mean BMI). Our study suggests that better primary care in the form of reduced list sizes per GP can improve the management of obesity.

JEL classification: I10; I12
Keywords: Obesity; GP supply; Primary care

1. Background

Obesity is a rapidly growing health problem that affects an increasing number of countries worldwide (WHO, 1998). In England in 1980 six per cent of males and eight per cent of females in England were obese; by 2003 the prevalence had trebled to 21 per cent and 24 per cent, respectively (Department of Health, 2003). The growth in obesity is a cause for concern because as well as being a debilitating condition in its own right, it is an important risk factor for a number of major diseases including coronary heart disease, type II diabetes, osteoarthritis, hypertension and stroke (NHLBI, 1998).

In the UK the treatment and prevention of obesity takes place mainly in primary care (National Audit Office, 2001). Evidence on the effectiveness is sparse and mixed: there have been few randomised controlled trials of primary care policies to reduce obesity (Harvey et al., 1999). Some commentators have argued that primary care interventions can reduce obesity. Finer (2003) suggests that the Counterweight Programme,[1] for example, is effective in reducing the burden of obesity in the community (Finer, 2003; Broom and Haslam, 2004; Counterweight Project Team, 2004a, 2004b). On the other hand, a recent randomised controlled trial found that offering practice teams a short training course in obesity management had little effect on patient weight (Moore et al., 2003). The House of Commons Health Committee recently argued that local GPs provide a unique resource for obesity management, but expressed concern that there is only limited prescribing of cost-effective obesity drugs, that specialist obesity services were commonly closed due to lack of funds, and that GPs and other primary care workers often prioritised other targets ahead of obesity (House of Commons Health Committee, 2004).

In this paper we use observational data to provide additional evidence on whether primary care interventions can reduce obesity. We do so by using very rich multi-level (individual and area) data to investigate whether, other things equal, individuals in areas with more GPs per head of population are less obese in terms of having a lower body mass index (BMI).

The approach we adopt is similar to that used in other multi-level studies to examine the overall effect of primary care on health. For example, Shi and Starfield (2000) found that individuals were more likely to report good health if they lived in states in the US with more primary care physicians per capita, after controlling for gender, age, ethnicity, employment, wages, deprivation, heath insurance, physical health and smoking. The data were from a 1996 sample of 58,000 respondents clustered in 60 communities. Shi, Starfield, Politzer and Regan (2002) used the same data source but in addition made use of responses to questions about accessibility of primary care, interpersonal care and continuity of care. The results were similar to Shi and Starfield (2000) in that better primary care was found to be associated with better physical and mental health after controlling for a wide range of covariates.

This literature has been concerned with general health rather than obesity and has not usually taken account of the endogeneity of primary care supply and health. We analyse the impact of the supply of GPs on individual BMI by regressing individual level BMI against health authority (HA) level GP supply and a large set of individual and HA level covariates. In our baseline model we use OLS. The major problem with this approach is endogeneity: GP supply may be associated with unobserved factors that are also associated with BMI. Other things equal, GPs like to live and work in “nice” areas and such areas have unobserved characteristics that lead them to have populations with lower BMI. This could lead to a positive estimated effect of GPs on BMI even if GP supply has no true effect. On the other hand, there may be a negative bias. GP location decisions are also affected by the GP remuneration system. Some types of payment are related to the mix of types of patient and the composition of the patient population varies across areas. Examples include capitation payments related to the age of patients and their deprivation levels, fee per item payments for such things as night visits and flu vaccinations for high risk groups, and payments for meeting quality targets. Thus it is possible that there may be higher rewards per patient in areas with a higher mean BMI. Hence it is possible that GP supply could be positively or negatively associated with BMI whether or not GP supply has an impact on BMI.

[1] http://www.counterweight.org

To test and control for endogeneity we use instrumental variables (IVs) for GP supply – observable characteristics that affect GP supply and are not correlated with unobserved factors affecting individual BMI. We use two area based instruments to estimate two stage last squares (2SLS) and mixed level IV models of the impact of GP supply on BMI.

2. Data and variables

2.1. Data sources

The main data source is the core sample of the Health Survey for England (HSE) 2000. The HSE is a nationally representative survey of individuals aged two years and over living in England. A new sample is drawn each year and respondents are interviewed on a range of core topics including demographic and socio-economic indicators, general health and psychosocial indicators, and use of health services. Additionally, there is a follow up visit by a nurse at which various physiological measurements are taken, including height and weight.

HA area level GP supply variables were constructed using the General Medical Services (GMS) database held by the National Primary Care Research and Development Centre (NPCRDC).[2] The database is a summary of data relating to GPs, their patients, partnerships and services for each registered general practice in England and Wales. A wide range of information is collected including the age and sex breakdown for each registered practice population, details of practice organisation such as staffing, list size, GP characteristics and details of service provision. We use data for six years from 1995-2000.

Additional area level data were assembled from three sources. First, we use the Allocation of Resources to English Areas (AREA) dataset for comprehensive data on deprivation and accessibility to health care services at the local authority (LA) ward level across England for the period 1996-2000 (Sutton et al., 2002; Gravelle et al., 2003). LA level data on crime rates in 2000 were obtained from the Neighbourhood Statistics branch of the Office for National Statistics,[3] and LA data on house prices for 2000 were obtained from the Land Registry.[4] The LA area level data were first converted to HA level based on 2001 HA boundaries. There were 95 HAs in England with a mean population of 515,517 residents (range 168,873 to 1,050,626). Mean values of the variables for each HA were computed based on the proportion of each LA ward's population resident within the HA. The HA data were then linked to the individuals in the HSE sample via their recorded HA of residence.

2.2. BMI and GP supply

The dependent variable is individual BMI, measured as weight in kilogrammes divided by height in metres squared (kg/m^2). This is computed from the height and weight measures obtained during the nurse visit. Thus BMI is not based on self reported height and weight, reducing the likelihood of systematic measurement error.

GP supply is computed at the HA level. All GPs working in practices with 100 patients or fewer were excluded from the data. GP supply is measured for each year 1995-2000 as the number of whole time equivalent (WTE) unrestricted principals or equivalents per 1,000 registered patients in each HA. Each GP practice p is located within a HA a. We compute for the p'th practice in HA a the number of patients in each year t (N_{apt}) and the number of WTE GPs (G_{apt}) and measure GP supply in HA a at year t as $1{,}000 * \Sigma_p G_{apt}/(\Sigma_p N_{apt})$.

2.3. Covariates

We include a large number of covariates, grouped in three categories. The first contains individual demographic variables, including gender, age, age squared and age cubed, plus interactions between age and gender. We also include ethnicity (nine categories), marital status (five categories), the number of infants living in the household aged zero or one year (three categories) and the number of children aged 2 to 15 years living in the household (seven categories).

[2] http://www.primary-care-db.org.uk/
[3] http://www.neighbourhood.statistics.gov.uk/home.asp
[4] http://www.landreg.gov.uk/propertyprice/interactive/ppr_ualbs.asp

The second category is individual socioeconomic variables. They include equivalised household income, social class of the head of the household (eight categories based on the Registrar General's classification), the highest educational level achieved (seven categories), car ownership (four categories) and housing tenure (five categories).

The third category is area level variables, taken mainly from the Indices of Deprivation 2000 (ID2000). There are forty six measures in all, including the overall ID2000 score plus the separate scores for each domain (which measure income deprivation, child poverty, employment deprivation, education deprivation, housing deprivation, and health deprivation).[5] We additionally include the proportion of the population receiving job seekers' allowance, the percentage of the population aged 17 or over not going to higher education, the proportion of attendance allowance claimants over 60 years, the proportion of income support claimants over 60 years, the proportion and standardised rate of incapacity benefit/severe disability allowance claimants, and the proportion and standardised rate of attendance allowance/severe disability allowance claimants (DTLR, 2000). In this category we also include data on area crime rates (separate rates for violent offences, sexual offences, robbery, burglary from a dwelling, theft of a motor vehicle, and theft from a motor vehicle) and twenty seven indictors measuring accessibility to health care in terms of waiting times for hospital services (acute, maternity, mental health, private health care, and outpatient services), the number of beds at local hospitals, distance to local hospitals, and the number of staff at local hospitals.

2.4. Instruments

In the IV models we instrument GP supply using two HA level variables. Both are observable area characteristics likely to affect GP supply but unlikely to influence BMI directly conditional on the rich set of other covariates in the BMI regression. The first IV is an index of local area house prices. This should affect the decision of GPs to locate in an area but is unlikely to be correlated with individual BMI directly. A priori we expect a negative partial correlation between house prices and GP supply. After experimenting with combinations of the prices of detached, semi-detached, terraced houses, and prices of flats, we use the area semi-detached house price, because it was the most significant predictor of GP supply conditional on the covariates.

The second instrument is the age related capitation payment per head of population. GPs receive capitation fees that increase with the age of the patient for each patient on their list. The age bands are 0-64; 65-74; and, 75+. Age related capitation payments are a major component of GP income in England. We expect to find more GPs in areas where the population generate higher age related capitation payments – that is, in areas where a higher proportion of the population are elderly, all else equal. Although age may be correlated with BMI at the individual level, we include individual age in the individual level BMI regression. It is difficult to think of any reason why the BMI of an individual patient, given their age and all the other individual and area factors included as covariates, should be correlated with the age structure of the area. The weighted average age related capitation payment per person in area *a* in year *t* is computed as $\sum_{k=1}^{3}\frac{N_{ka}}{N_a}Q_{kt}$,where N_{ka} is the number of people in HA *a* in age band *k*, and Q_{kt} is the capitation payment for age band *k* in year *t*. The values of $Q_{.kt}$ were obtained for each year from 1995 to 2000 from the Statement of fees and Allowances Payable to General Medical Practitioners in England and Wales (Department of Health 2000). The proportion of the HA population in each age band was obtained for 2000 from the AREA dataset.

[5] We exclude the access domain score since it includes a measure of GP supply.

3. Estimation

3.1. Regression models

In the baseline models we use OLS to regress BMI against GP supply and the covariates. In the IV models we use two alternative approaches. In the first we estimate a GP supply equation at the individual level, regressing GP supply in each year against the two instruments plus the individual and area covariates. This yields predicted GP supply for each individual in each year and individuals in each area can have different predicted supplies. In the second stage individual BMI is regressed against individual predicted GP supply plus the individual and area covariates. In the second approach the first stage GP supply equation is estimated at the HA level to produce a predicted GP supply measure which is the same for all individuals in the HA. The second stage individual BMI equation is estimated using OLS, and includes individual and area covariates as well as the HA predicted GP supply. The first approach is the standard two stage least squares (2SLS) model. The second we label a 'mixed level IV' approach.

The standard errors in the second stage of the 2SLS models are based on the asymptotic covariance matrix given in Wooldridge (2002, p.95). The standard errors in the second stage of the mixed level model are corrected to account for the two stage nature of the estimation process using a bootstrapping procedure. We first compute weights for each individual observation in the HSE sample equal to the population of the HA in which they live divided by the number of HSE observations in each HA. Applying these weights allows us to run the GP supply equation on the individual level data and obtain the same coefficients as would be obtained by running the GP supply equation at the HA level. We draw a full sample with replacement from the individual level dataset and estimate the GP supply equation on the individual level data using the weights. We include the predicted GP supply variable in the second stage individual BMI regression along with the covariates. We repeat the procedure 1,000 times and calculate the standard deviation of the distribution of the 1,000 GP supply coefficients as a measure of the standard error.

For each of the three models (OLS, 2SLS, mixed level IV) we report six separate regressions, examining the effect on obesity in 2000 of the separate impact of GP supply measured in each year over the six year period 1995-2000, plus the covariates. In total we report results for 3*6 = 18 BMI regressions.

3.2. Sample size and sampling issues

The total core sample size in the HSE in 2000 is 9,920. Excluding pregnant women (82 observations), and all individuals less than 18 years of age (2,159 observations), reduced the sample to 7,679. 920 observations were then excluded because they had invalid BMI measures: due to "Height/weight/BMI not useable" (122), "Height/weight refused" (417), "Height/weight attempted but not obtained" (99), and "Height/weight not attempted" (282). The final estimation sample was 6,759.

Following Moulton (1990), who demonstrates the pitfalls in failing to control for within area dependence when estimating the effects of area level variables on individual level outcomes, we adjust the standard errors in the OLS and 2SLS models to control for HA level clustering.

In all the BMI regressions we included a selection bias correction term to control for non-random missing BMI values. We used a binary indicator of whether an individual has missing BMI data as the dependent variable in a probit regression on the full set of covariates. We computed the inverse Mills ratio for each observation and included it in the individual level BMI models.

The HSE sample had missing values for the income variable (16% had missing values), and the ethnicity, social class, education, and car ownership variables (each had less than 1% missing values). To maximise the sample size we imputed missing values for these variables. Missing values for income were imputed using the linear prediction from a regression of income on the other covariates. For binary and categorical variables, missing values were assigned to the omitted category. To allow for the possibility that items were not missing at random we included dummy variable for all imputed items to indicate item non response. We use this approach in preference to other methods for dealing with missing data, such as hotdecking, because items may not be missing at random. If the missing item dummy variable is insignificant, non-responders' BMI is affected by the imputed variable in the same way as the responders, and the imputation has increased sample size without biasing results. If the dummy variable is significant then responders and non-responders are affected in different ways by the variable, and inclusion of the missing item dummy variable enables estimation of an effect for responders that is not contaminated by the imputation for non responders.

4. Results

4.1. Descriptive statistics

Table 1 contains population weighted health authority level summary statistics for WTE GPs per 1,000 patients over the period 1995 to 2000. From the top panel, in each year the mean value is similar, with around 0.5 WTE GPs per 1,000 registered persons, or one WTE GP for every 2,000 people. The similarity in the distributions suggests that GP supply varied little over the period. The bottom panel of Table 1 shows that the measures are highly positively correlated, and the correlation coefficient is statistically significant.

Table 1. GP supply measures

	1995	1996	1997	1998	1999	2000
Distributions						
Observations	95	95	95	95	95	95
Mean	0.503	0.500	0.502	0.502	0.505	0.501
Std. Dev.	0.033	0.034	0.034	0.034	0.030	0.033
Minimum	0.432	0.432	0.430	0.436	0.449	0.431
25^{th} percentile	0.480	0.476	0.481	0.481	0.484	0.481
Median	0.498	0.497	0.496	0.496	0.500	0.495
75^{th} percentile	0.523	0.522	0.517	0.517	0.519	0.517
Maximum	0.591	0.593	0.595	0.594	0.598	0.596
Correlation coefficients						
1996	0.982*	1.000				
1997	0.964*	0.979*	1.000			
1998	0.952*	0.969*	0.986*	1.000		
1999	0.899*	0.911*	0.921*	0.933*	1.000	
2000	0.932*	0.942*	0.955*	0.966*	0.918*	1.000

* p<0.00001

The sample distribution of BMI is in Table 2; histograms for male and female BMI are in Figure 1. The mean BMI in the sample is 26.8 kg/m^2. Only 34% of the sample has a BMI within the range usually considered to be healthy (20 to 25 kg/m^2), while 22% and 6% meet the standard definitions of obesity (BMI over 30 kg/m^2) and morbid obesity (BMI over 35 kg/m^2), respectively. The modal BMI category is overweight (25 to 30 kg/m^2), containing 40% of the sample.

Table 2. Body mass index obesity measure (6,759 observations)

Variable	Mean	Std. Dev.
BMI (kg/m^2)	26.838	4.903
BMI < 20	0.045	0.208
20 ≤ BMI < 25	0.343	0.475
25 ≤ BMI < 30	0.395	0.489
30 ≤ BMI < 35	0.156	0.363
35 ≤ BMI < 40	0.045	0.207
BMI ≥ 30	0.217	0.412
BMI ≥ 35	0.060	0.238
BMI ≥ 40	0.016	0.124

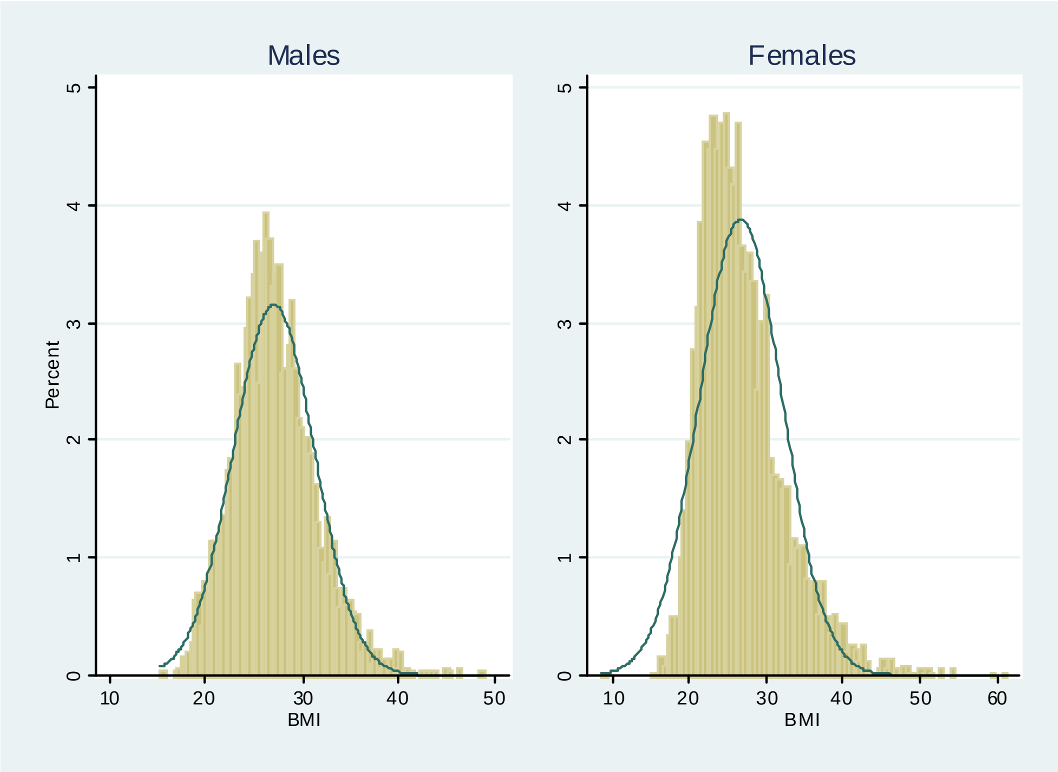

Figure 1. Distribution of BMI (kg/m^2) for males and females

4.2. GP supply equations

The key results from the GP supply equations are in Table 3, which reports the coefficients, and the individual and joint significance of the two instruments on GP supply in each year conditional on the covariates. The top panel shows the results from the individual level analysis used in the first stage of the 2SLS models. The bottom panel shows the results from the area level analysis used in the mixed level IV models. In all cases the instruments have the expected sign (mean age related capitation payments have a positive impact on GP supply and house prices have a negative effect), and are individually and jointly significant. The coefficients are of a similar order of magnitude in the two sets of models, though their significance is greater in the individual level analyses. This is unsurprising given the number covariates and the relatively small sample size in the area level models.

4.3. BMI equations

The key results from the BMI equations are in Table 4. The coefficients on the GP supply variable and related measures of statistical significance are reported. The elasticity of BMI with respect to changes in GP supply is also presented, computed at the sample mean.[6] The table also reports the explanatory power of the OLS models and the second stage of the mixed level IV models. In the 2SLS models we report the results of Hansen J tests of overidentifying restrictions (a p–value < 0.05 casts doubt on the validity of the instruments) and Hausman F tests for exogeneity (a p–value < 0.05 indicates that IV estimators should be used in preference to OLS estimators).

---

[6] The estimated BMI equation is of the form $\hat{y}_i = \hat{\delta} g_i + \hat{\beta} x_i$ where *y* is BMI, *g* is GP supply, *x* is a set of covariates, δ and β are estimated coefficients, and *i* indexes individuals. The elasticity is $(dy/dg)g/y = \hat{\delta} g/y$, which is estimated at the sample mean values of *g* and *y*.

Table 3. The impact of the instruments on GP supply

	1995 Coef.	1995 t	1996 Coef.	1996 t	1997 Coef.	1997 t	1998 Coef.	1998 t	1999 Coef.	1999 t	2000 Coef.	2000 t
Individual level analysis [1]												
Mean age related capitation payment	0.089	5.59	0.102	6.84	0.107	7.54	0.101	6.59	0.078	5.82	0.070	4.80
Semi-detached house price / 100,000	-0.010	-3.47	-0.010	-3.50	-0.013	-3.86	-0.014	-3.69	-0.017	-4.90	-0.012	-4.08
F-test instruments = 0 [p-value]	22.29 [<0.001]		33.01 [<0.001]		41.97 [<0.001]		32.61 [<0.001]		36.07 [<0.001]		19.63 [<0.001]	
Observations	6,759		6,759		6,759		6,759		6,759		6,759	
R^2	0.9103		0.9099		0.9087		0.8894		0.8648		0.8638	
Area level analysis [2]												
Mean age related capitation payment	0.088	3.84	0.097	4.15	0.103	4.51	0.094	3.80	0.074	3.31	0.065	2.75
Semi-detached house price / 100,000	-0.010	-1.98	-0.010	-1.89	-0.012	-2.34	-0.013	-2.25	-0.017	-2.96	-0.012	-1.95
F-test instruments = 0 [p-value]	9.07 [<0.001]		10.11 [<0.001]		12.53 [<0.001]		9.46 [<0.001]		9.52 [<0.001]		5.50 [0.007]	
Observations	95		95		95		95		95		95	
R^2	0.9102		0.9061		0.9034		0.8840		0.8587		0.8593	

[1] Individual level covariates are also included for age, gender, income, car ownership, social class of head of household, educational attainment, ethnic group, marital status, housing tenure, number infants 0 to 1 years in household, number children 2 to 15 years in household, and item non-response. Area level covariates are also included that measure crime rates, deprivation, and the supply of health services. In all the models the standard errors are adjusted for area level clustering.

[2] Area level covariates are also included that measure crime rates, deprivation, and the supply of health services

Table 4. The impact of GP supply on BMI (kg/m^2)

GP supply	OLS Coef.	OLS t	OLS Elast.	OLS R^2	2SLS Coef	2SLS z	2SLS Elast.	2SLS Hansen J test [p-value]	2SLS Hausman F-test [p-value]	Mixed level IV Coef.	Mixed level IV Coef./ Std.Err.	Mixed level IV Elast.	Mixed level IV R^2
1995	-2.675	-0.75	-0.050	0.0924	-25.116	-2.72	-0.472	1.19 [0.27]	7.33 [0.01]	-25.850	-2.64	-0.486	0.0933
1996	-5.543	-1.69	-0.104	0.0925	-21.840	-3.02	-0.409	1.01 [0.32]	5.72 [0.02]	-23.397	-2.75	-0.438	0.0933
1997	-6.082	-1.93	-0.114	0.0926	-19.279	-3.07	-0.362	1.61 [0.20]	5.24 [0.02]	-20.212	-2.54	-0.379	0.0933
1998	-5.445	-1.89	-0.102	0.0926	-19.374	-3.02	-0.364	1.96 [0.16]	4.67 [0.03]	-20.675	-2.50	-0.388	0.0932
1999	-4.643	-1.52	-0.088	0.0925	-18.961	-2.77	-0.358	3.19 [0.07]	4.49 [0.03]	-19.185	-2.14	-0.362	0.0930
2000	-5.329	-1.58	-0.010	0.0926	-23.152	-2.85	-0.434	2.20 [0.14]	4.43 [0.04]	-24.338	-2.48	-0.456	0.0931

The number of observations in every model is 6,759.
In all the models individual level covariates are also included for age, gender, income, car ownership, social class of head of household, educational attainment, ethnic group, marital status, housing tenure, number infants 0 to 1 years in household, number children 2 to 15 years in household, and item non-response. A selection bias correction term (inverse mills ratio) for non-random missing BMI values is also included. Area level covariates are also included that measure crime rates, deprivation, and the supply of health services.
In the OLS and 2SLS models the standard errors are adjusted for area level clustering. In the mixed level IV models the standard error is the standard deviation of the coefficient from 1,000 replications

Conditional on the covariates, the OLS results indicate that GP supply has a negative but generally weakly significant effect on BMI. In contrast, the IV models (2SLS and mixed level IV) show a negative and significant effect in all cases. The overidentifying restrictions tests indicate that, insofar as it can be tested empirically, the instruments are not correlated with the error term in the BMI equation. The exogeneity tests indicate that IV models should be preferred to the OLS models.

It is not possible to determine if the effect of GP supply operates with a lag since there is little variation in the coefficients on the GP supply variable at different lags or in their statistical significance. This is probably because GP supply did not vary much within areas over the period (see Table 1).

The elasticities indicate that a 10% increase in GP supply is correlated with a 3.58% to 4.72% decrease in BMI in the 2SLS models, depending on the year, and a 3.62% to 4.86% decrease in the mixed level IV models. At the sample mean BMI, an elasticity of 4% implies that a 10% increase in GP supply is associated with a reduction in BMI of around 1 kg/m^2.

Table 5 presents coefficients on selected covariates from one of the BMI equations – the 2SLS model with GP supply in 2000 plus the full set of covariates. Results in the other BMI equations are similar. Age has a non-linear effect on BMI in both sexes. Figure 2 plots predicted BMI against age for both sexes using the coefficients in Table 5. Conditional on the other covariates, there is an inverse U-shape between BMI and age for both males and females. For males BMI and age are positively correlated up to 49 years of age and negatively correlated thereafter. For females the turning point occurs at 61 years of age. Income has a negative but insignificant effect on BMI. Relative to the professional classes, other social classes tend to have higher BMI, with a significant effect in the semi-skilled manual group. Those who are less well educated are found to have significantly higher BMI, with the biggest effect in those with no qualifications. Some Black ethnic groups have significantly higher BMI than Whites, while those in Indian, Pakistani, Bangladeshi and Chinese ethnic groups have lower BMI, all else equal. Individuals who are married, separated or widowed have higher BMI than those who are single. The coefficients on the other variables not reported in the table are generally insignificant.

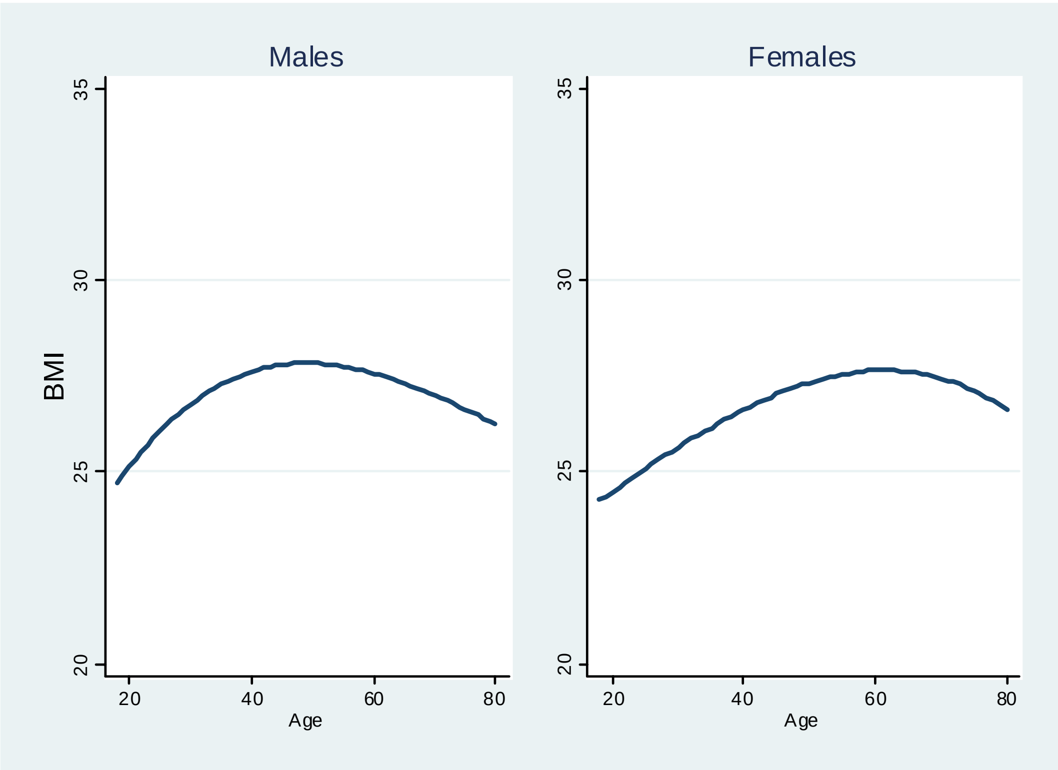

Figure 2. Conditional impact of age on BMI (kg/m^2)

Table 5. The partial impact of selected covariates on BMI (kg/m^2)

Covariates	Coef.	z
GP supply (2000)	-23.152	-2.85
Age/100	42.860	4.99
Age/100 squared	-62.901	-3.64
Age/100 cubed	26.090	2.40
Female	3.302	1.67
Female*Age/100	-32.365	-2.49
Female*Age/100 squared	72.281	2.73
Female*Age/100 cubed	-45.523	-2.70
Income/100,000	-0.454	-1.16
Social class of head of household [1]		
II Managerial/technical	-0.015	-0.06
IIIn Skilled non-manual	0.145	0.46
IIIm Skilled manual	0.336	1.11
IV Semi-skilled manual	0.677	2.20
V Unskilled manual	0.593	1.36
Other	0.837	1.77
Education [2]		
Higher education less than a degree	0.417	1.54
A level or equivalent	0.360	1.61
GCSE or equivalent	0.472	2.15
CSE or equivalent	0.643	2.14
Other qualification	0.274	0.84
No qualification	0.800	2.79
Ethnic group [3]		
Black Caribbean	1.661	3.32
Black African	-0.744	-0.76
Indian	-1.081	-3.26
Pakistani	-1.056	-1.95
Bangladeshi	-2.138	-3.51
Chinese	-1.991	-2.49
Other non-white ethnic group	-0.068	-0.17
Marital status [4]		
Married	1.130	5.60
Separated	0.851	1.97
Divorced	0.363	1.23
Widowed	1.117	3.62
Observations	6,759	

[1] The omitted category is I Professional.
[2] The omitted category is Degree.
[3] The omitted category is White.
[4] The omitted category is Single.
Coefficients are from the 2SLS regression of individual BMI on instrumented GP supply and a full set of covariates.
Individual level covariates are also included for housing tenure, car ownership, number infants 0 to 1 years in household, number children 2 to 15 years in household, and item non-response. A selection bias correction term (inverse mills ratio) for non-random missing BMI values is also included. Area level covariates are also included that measure crime rates, deprivation, and the supply of health services.
The standard errors are adjusted for area level clustering.

We also investigated whether the impact of GP supply on BMI was constant across the BMI distribution. We did this by first constructing an individual level ordinal variable based on six categories of BMI.[7] We then regressed this variable against GP supply and the full set of covariates using a generalised ordered logit model that adjusted for area level clustering. We tested whether GP supply had a different impact in different BMI categories (the parallel regression assumption) using a Brant test (Brant, 1990). The null hypothesis is that the coefficient on the GP supply variable is the same in each BMI category. A p–value < 0.05 indicates that the impact of GP supply is significantly different for individuals in different BMI categories. The GP supply variable in the generalised ordered logit models was obtained from a first stage GP supply equation estimated at the HA level for each year 1995–2000. We estimated six generalised ordered logit models using this mixed level IV approach, for each year in which GP supply was measured. In all cases the p-value was > 0.05. We fail to reject the null hypothesis that the coefficients on the GP supply variable were not significantly different in the different BMI categories.

5. Concluding remarks

We have investigated the impact of GP supply on BMI in England using multiple regression models with a rich set of individual and area variables. Using IVs to control for endogeneity we found that GP supply has a statistically significant and negative effect on BMI. On average, a 10% increase in GP supply in a Health Authority is associated with a reduction in BMI of around 1 kg/m^2.

The impact of GP supply in the IV models is more negative than in the OLS models, which suggests that unobserved heterogeneity leads to an underestimation of the negative effect of GP supply on BMI. This indicates that there are omitted variables that are positively correlated with both GP supply and BMI. For example, it may be that GPs are influenced by financial incentives that encourage them to locate in areas that have high BMI.

The major limitation of our study is that although we find evidence of a negative relationship between GP supply and BMI we cannot provide any information on the mechanisms by which increases in GP supply might reduce BMI. For example, do GPs have more time to spend on the management of obese patients? Do they change their methods of management? Is increased provision of GPs merely a proxy for increased provision of other members of the primary care team, such as nurses and dieticians, who may have more impact on BMI? Data limitations preclude us from investigating these issues. The HSE asks respondents about their use of GP services only in the previous two week period and does not contain information on the quality of services provided. The GMS GP workforce census has little reliable information about skill mix in general practices. A recent report published by the NHS Alliance (2005) suggests some mechanisms by which primary care can be instrumental in reducing obesity, highlighting examples of best practice in managing obesity in primary care across England. Strategies include training primary care and other staff to encourage high quality physical activity in schools at lunchtime, setting individual targets for adults for sustained reduction in body weight over a year, offering GP surgery appointments specifically for weight advice, referral by GPs to specialist clinics for patients with substantial weight gain, providing vouchers offering discounts for fruit and vegetable purchases at local shops, and distributing fruit and fruit drinks in practice waiting rooms. If, plausibly, measures such as these are more prevalent in areas with better GP supply then this suggests some mechanisms by which increases in GP supply might reduce BMI. However, this is conjecture, and further research would be beneficial.

There is previous conflicting evidence of the impact of primary care on obesity. This study provides some support for the view that improved primary care provision in the form of reduced list sizes per GP can lead to a reduction in BMI.

[7] The ordinal categories were BMI < 20 kg/m^2, 20 $kg/m^2 \leq$ BMI < 25 kg/m^2, 25 $kg/m^2 \leq$ BMI < 30 kg/m^2, 30 kg/m^2 $\leq$BMI < 35 kg/m^2, 35 $kg/m^2 \leq$ BMI < 40 kg/m^2 and BMI $\geq$ 40 kg/m^2.

References

Brant, R., 1990. Assessing proportionality in the proportional odds model for ordinal logistic regression. *Biometrics* 46, 1171–1178.

Broom, J., Haslam, D., 2004. Programme to fight obesity in primary care already exists. *BMJ* 329, 53.

Counterweight Project Team, 2004a. Current approaches to obesity management in UK Primary Care: the Counterweight Programme. *J Hum Nutr Diet* 17, 183–190.

Counterweight Project Team, 2004b. A new evidence-based model for weight management in primary care: the Counterweight Programme. *J Hum Nutr Diet* 17, 119–208.

Department of Health, 2000. *Statement of Fees and Allowances Payable to General Medical Practitioners in England and Wales*. Department of Health.London.

Department of Health, 2003. *Health survey for England, 2001: a survey carried out on behalf of the Department of Health.* The Stationery Office, London.

Department of Transport, Local Government and the Regions [DTLR], 2000. *Measuring multiple deprivation at the small area level: the Indices of Deprivation 2000*. DTLR, London.

Finer, N., 2003. Management of obesity in primary care. *BMJ.com*, 14 November 2003 [letter].

Gravelle, H., Sutton, M., Morris, S., Windmeijer, F., Leyland, A., Dibben, C., Muirhead, M., 2003. A model of supply and demand influences on the use of health care: implications for deriving a ‘needs-based’ capitation formula. *Health Economics* 12, 985–1004.

Harvey, E.L., Glenny, A.M., Kirk, S.F.L., Summerbell, C.D., 1999. A systematic review of interventions to improve health professionals’ management of obesity. *International Journal of Obesity* 23, 1213–1222.

Moore, H., Summerbell, C.D., Greenwood, D.C., Tovey, P., Griffiths, J., Henderson, M., Hesketh, K., Woolgar, K., Adamson, AJ., 2003. Improving management of obesity in primary care: cluster randomised trial. *BMJ* 327, 1085-1090.

Moulton, B.R., 1990. An illustration of a pitfall in estimating the effects of aggregate variables on micro units. *Review of Economics and Statistics* 72, 334-348.

National Audit Office, 2001. *Tackling obesity in England*. Report by the Comptroller and Auditor General, HC220. The Stationery Office, London.

House of Commons Health Committee, 2004. *Obesity: third report of session 2003-4, Volume I, report, together with formal minutes.* The Stationery Office, London.

National Heart, Lung and Blood Institute [NHLBI], 1998. *Clinical guidelines on the identification, evaluation and treatment of overweight and obesity in adults,* NIH publication number 98-4083. National Institutes of Health, New York.

NHS Alliance, 2005. *Commissioning obesity services: PCTs’ services and strategies*. NHS Alliance, London.

Shi, L., Starfield, B., 2000. Primary care, income inequality, and self-rated health in the Untied States: a mixed-level analysis. *Int J Health Serv Research* 30, 541–555.

Shi, L., Starfield, B., Politzer, R., Regan, J., 2002. Primary care, self-rated health, and reductions in social disparities in health. *Health Serv Res* 37, 529-550.

Sutton, M., Gravelle, H., Morris, S., Leyland, A., Windmeijer, F., Dibben, C., Muirhead, M., 2002. *Allocation of Resources to English Areas: Individual and Small Area Determinants of Morbidity and*

Use of Health Care. Report for Department of Health Information and Statistics Division, Common Services Agency, Scotland.

Wooldridge, J., 2002. *Econometric analysis of cross-section and panel data*, MIT Press, Cambridge, Massachusetts.

World Health Organization [WHO], 1998. *Obesity: Preventing and Managing the Global Epidemic*. WHO, Geneva.